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Coordination Models and Techniques for Big Data and Machine Learning Systems

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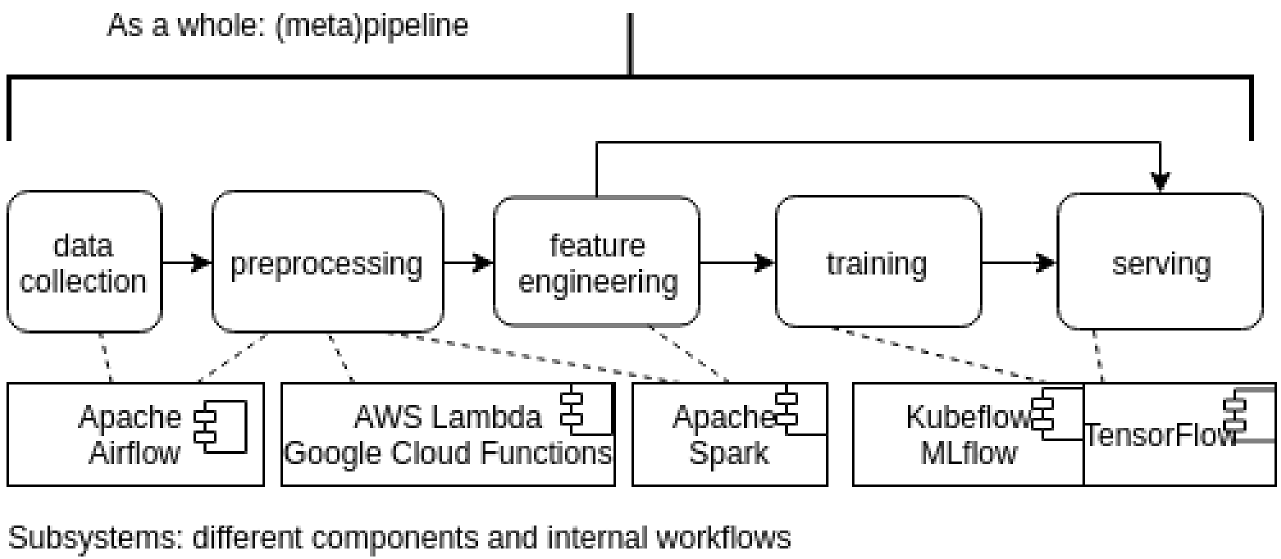
Learning objectives

- Analyze the role of coordination techniques, their complexity and diversity in big data/ML systems
- Understand and apply orchestration models, common tools and design patterns
- Understand and apply choreography models, common tools and design patterns
- Understand, define and develop ML model serving

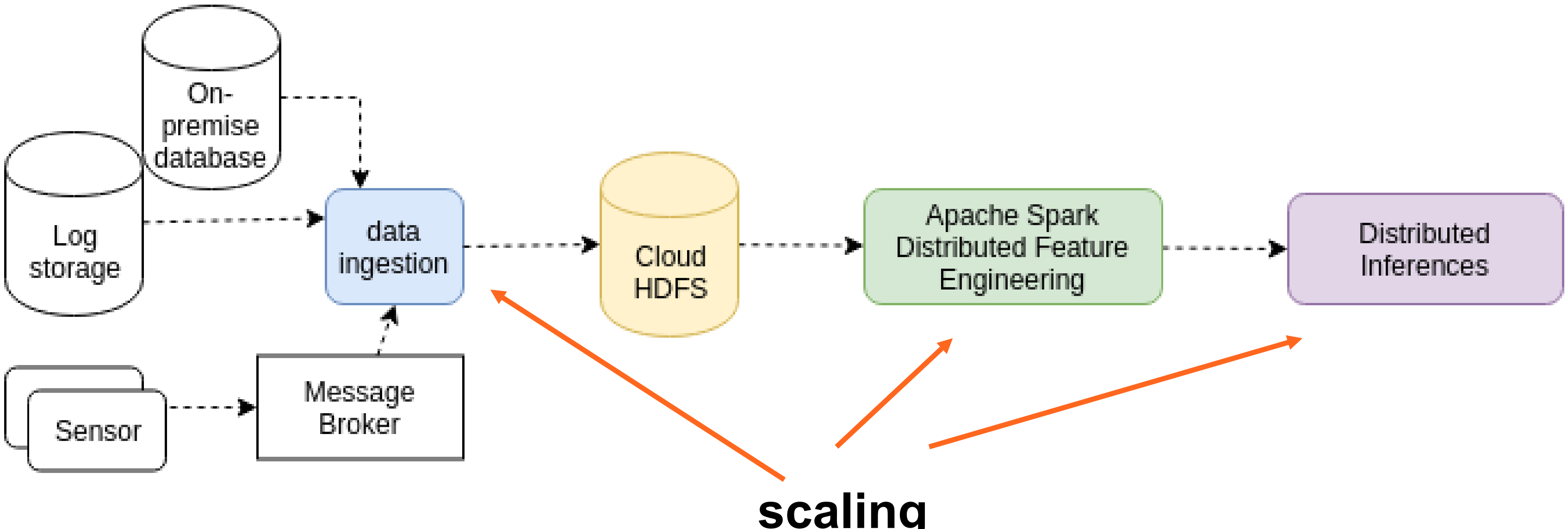
Recall: big data/ML systems

- **Multiple levels:**
  - Meta-workflow or -pipeline
  - Inside each phase: pipeline/workflow or other types of programs



Automation vs manual tasks: share your current way? How much automation do you have?

Think about some key metrics, like high throughput and service time for inferences. If you want your service to be fast? What will you do?



Where can we scale our ML systems?

- **Scale data processing**
  - is the data in data preparation/feature engineering big data?
- **Scale training and serving tasks**
  - distributed and parallel processing
- **Scaling needs monitoring**
  - logging, tracing, monitoring of infrastructures, consumer requests and ML/big data tasks
- **Scaling needs coordination**
  - orchestration or choreography techniques

Coordination complexity and diversity

Main issues related to coordination

- **Differences between the coordination of phases and of tasks in big data/ML systems**
  - Locality, dependencies and granularity
- **Different types of software artefacts and resources for big data/ML systems**
  - management and on-demand provisioning
- **Distributed computing in training, testing and experimenting**
  - trial computing configurations, inputs/results collection
- **Various observability and layers related to R3E for the pipeline execution**
  - end-to-end R3E requires coordination

W3H: what, when, where and how for coordination

Where: within a phase, across phases, within a component, a subsystem, etc.

What: preparing data and machines, performing inferences, carrying out observability

When: triggered by data flows or control flows or events? Internal triggers vs external triggers

How: which tools, models?

Coordination

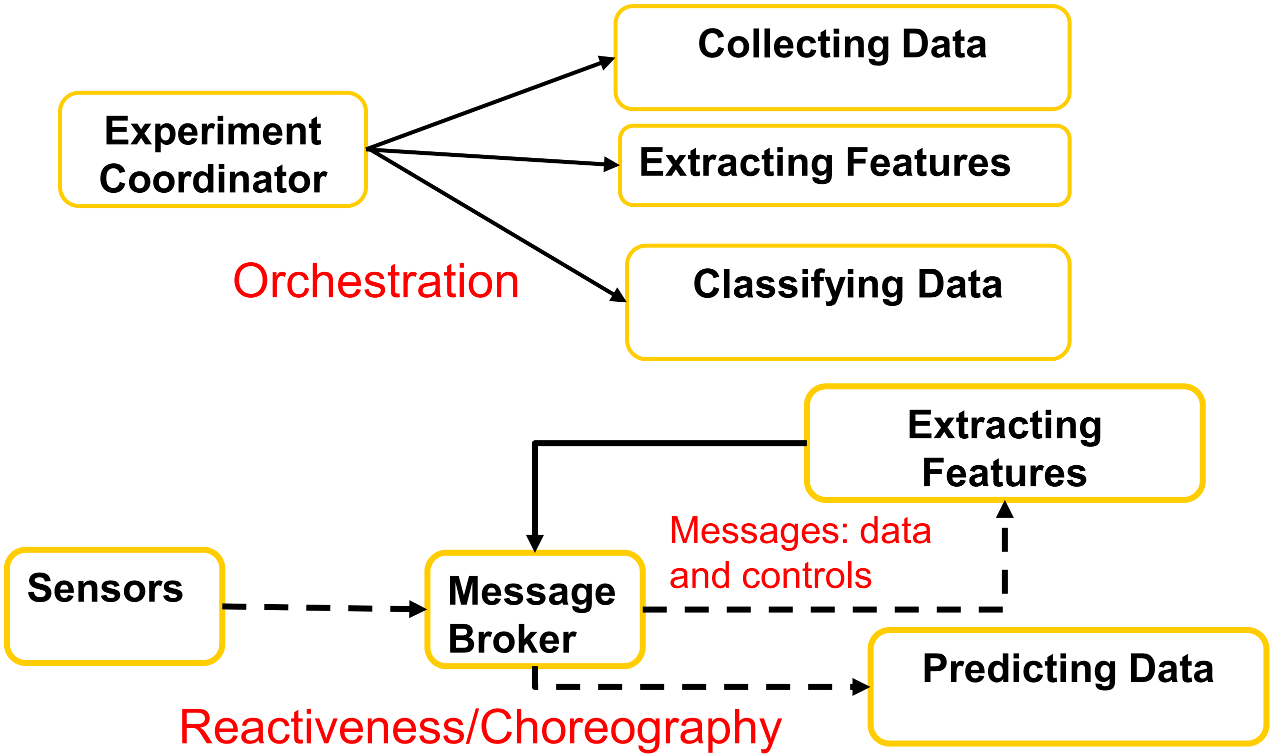
Diversity and complexity

- **Diversity**
  - so many tools/frameworks in a single big data/ML system
    → *a single coordination model/tool might not be enough*
  - there exist many coordination systems (included your specific implementation)
    → *which ones should we select?*
- **Complexity, due to the large-scale**
  - integration models with big data/ML components and infrastructures
  - runtime management: performance, failures, states

Coordination styles

- **Coordination models for Big Data/ML systems**
  - orchestration and reactiveness/choreography
- **Orchestration**
  - task graphs and dependencies are based on control or data flows
  - ddedicated orchestrator: tasks triggered based on completeness of tasks or the availability of data
- **Reactiveness/choreography**
  - follow reactive model: tasks are reacted/triggered based on messages

Orchestration and reactiveness



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Coordination for ML/big data pipelines

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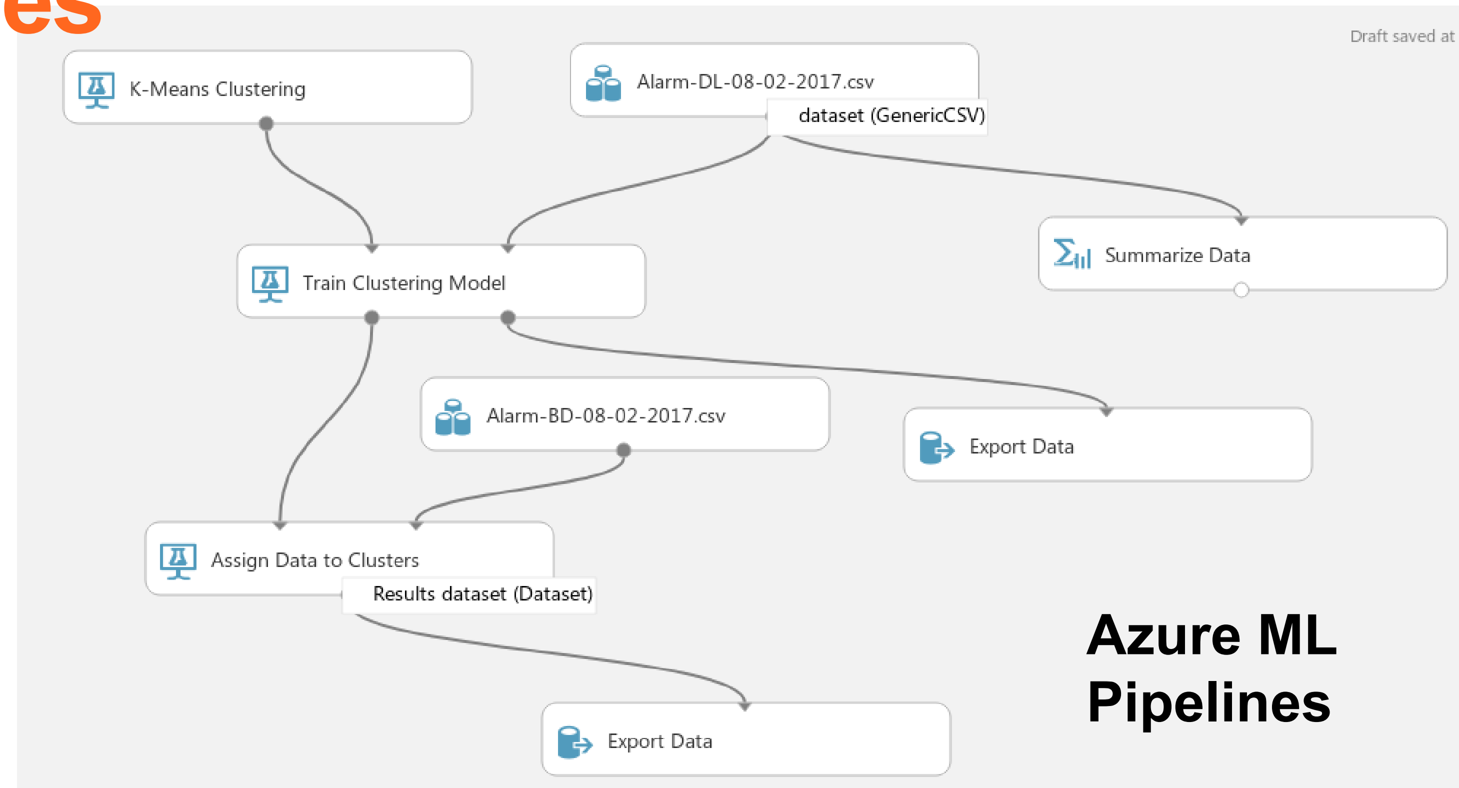
Coordination with workflow techniques

The orchestration style

Orchestration architectural style: design

- **Workflow architectures are well-known**
  - Big Data/ML systems: leverage many types of services and cloud technologies
- **Required components**
  - workflow/pipeline specifications/languages (also UI)
  - data and computing resource management, external services
  - orchestration engines (with different types of schedulers)
- **Execution environments**
  - cloud platforms (e.g., VMs, containers, Kubernetes)
  - heterogenous computing resources (PC, servers, Raspberry PI, etc.)

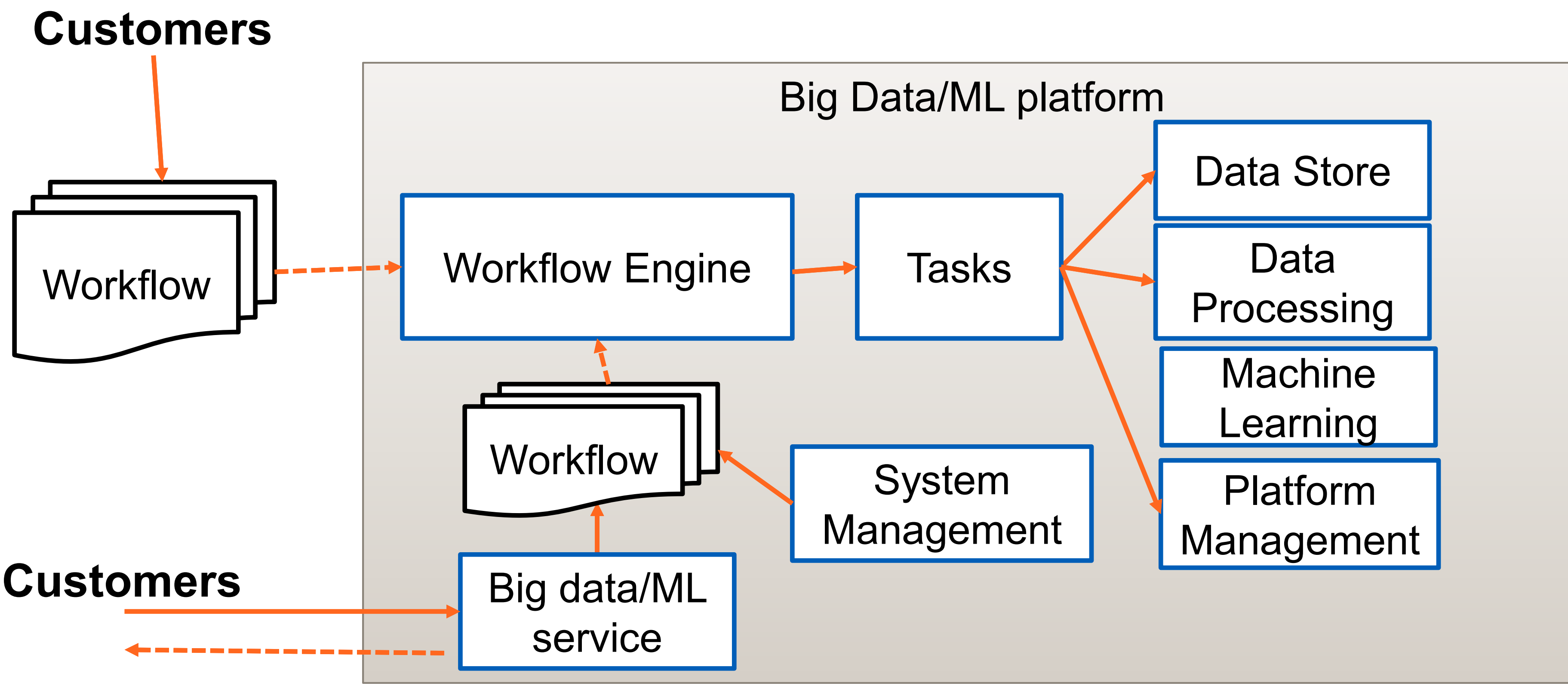
Example: workflow used in ML pipelines



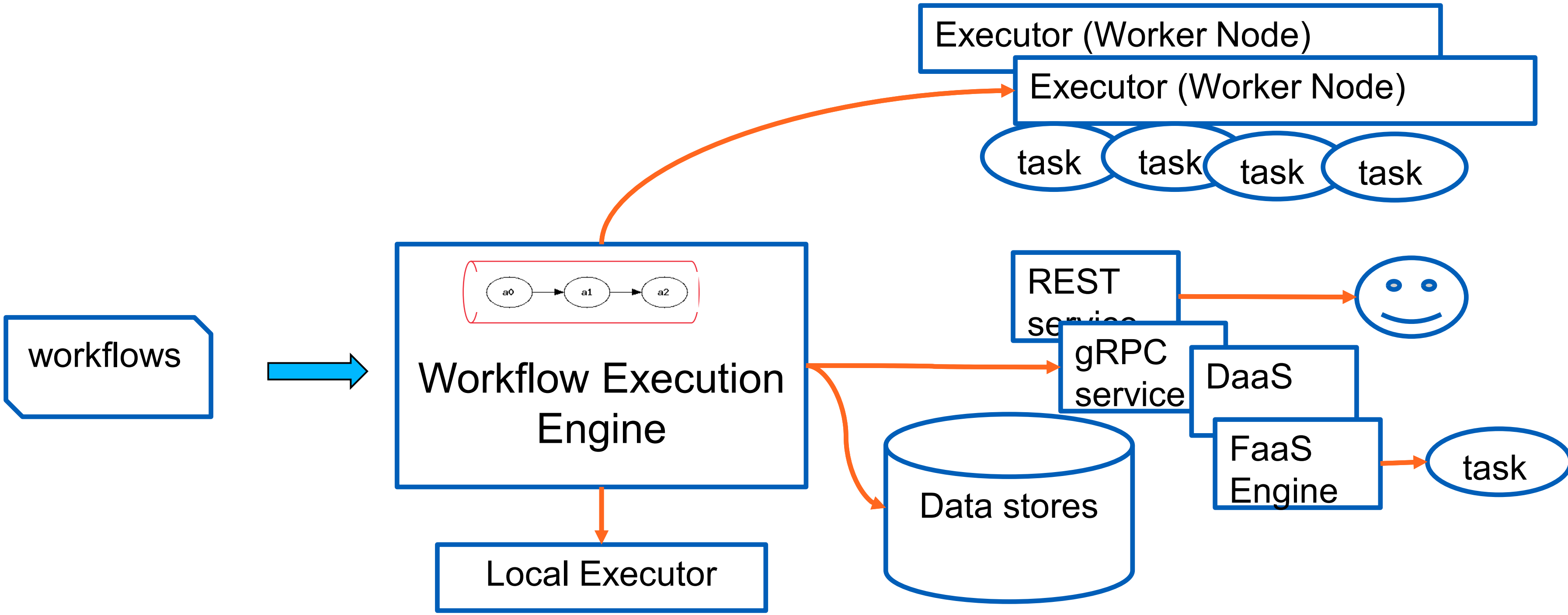
So what is behind the scene?

Azure ML Pipelines

Workflows in big data/ML systems



Common workflow execution models



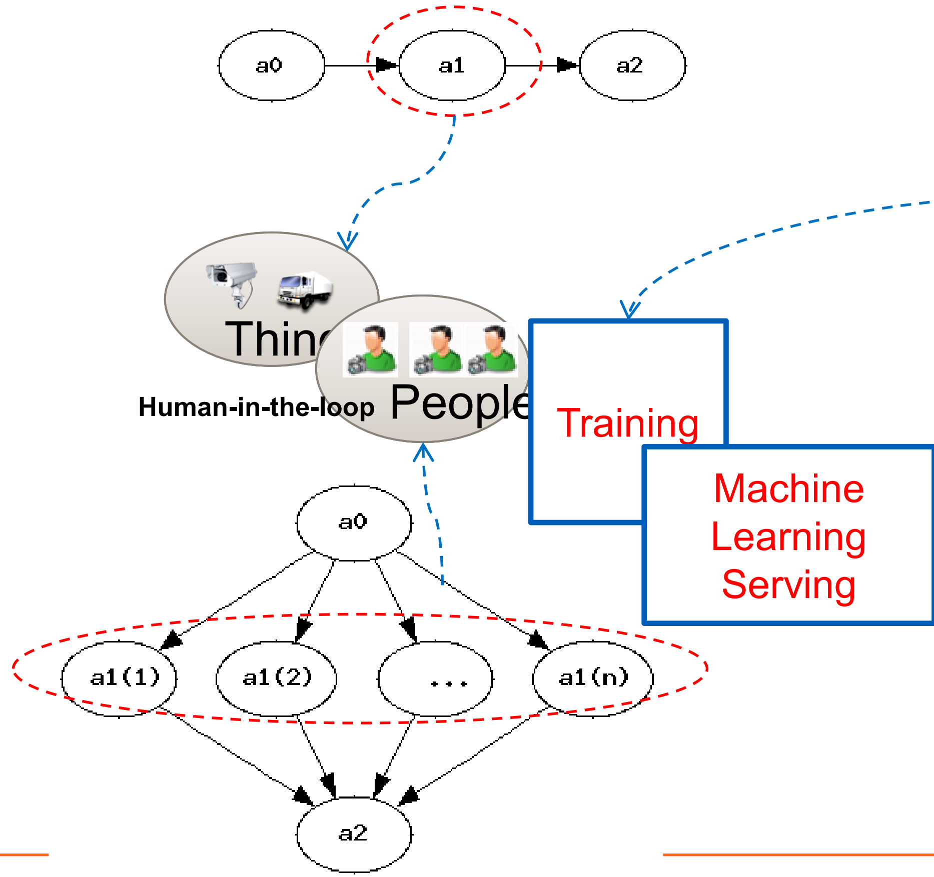
Executors: containers, common OS processes, Spark, …

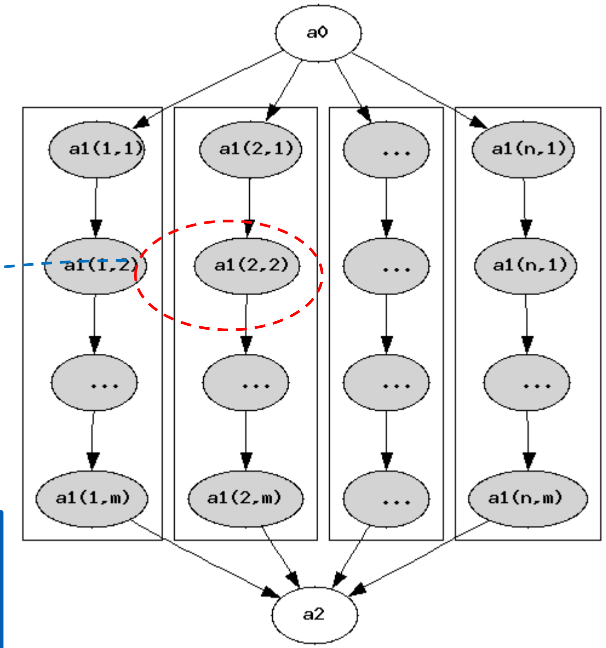
Resource management: Kubernetes, OpenStack, Batch Job Scheduler

Key components

- **Tasks/activities**
  - describe a single work (it does not mean small)
  - tasks can be carried out by humans, executables, scripts, batch applications, stream applications, and Web services.
- **Workflow languages**
  - how to structure/describe tasks, dataflows, and control flows
- **Workflow engine**
  - execute the workflow by orchestrating tasks
  - usually call remote services to run tasks

Tasks orchestration, e.g. in ML





Things: edge ML/tinyML
People: Human-in-the-ML loop

Runtime aspects

- **Parallel and distributed execution**
  - tasks are deployed and running in different machines
  - multiple workflows are running in the same set of machines (multi-tenancy)
- **Long running**
  - can be hours! → resilient, debugging, logging
- **Checkpoint and recovery, monitoring and tracking**
  - which tasks are running, where are they?
- **Data exchange**
- **Stateful management**
  - dependencies among tasks w.r.t control and data

Data exchange among tasks

- **Data and systems conditions**
  - big files/big dataset, small/fast data (e.g., in realtime ML), etc.
  - shared nothing or not among computing resources
- **Some mechanisms**
  - shared file systems/data volume
    - *Can be read/write only or one or many*
  - middleware: object/blob storage (like S3 style)
  - collective communications among tasks – using high-level libraries (e.g., Gloo, MPI, NCCL)
  - direct exchange (e.g., know your target)
  - messaging

Describing workflows

- **Programming languages with procedural code**
  - general- and specific-purpose programming languages, such as Java, Python, Swift
  - common ways in big data and ML platforms
- **Descriptive languages with declarative schemas**
  - BPEL, YAML, and several languages designed for specific workflow engines
  - common in business and scientific workflows
  - YAML is also popular for big data/ML workflows in native cloud environments

Workflow frameworks

- **Generic workflows**
  - use to implement different tasks, such as machine provisioning, service calls, data retrieval
  - Examples: Airflow (https://airflow.apache.org), Argo Workflows (https://argoproj.github.io/argo), Prefect (https://www.prefect.io), Uber Cadence (https://github.com/uber/cadence)
- **Specific workflows for specific purposes**
  - E.g., Kubeflow (https://github.com/kubeflow/pipelines)
  - Recent serverless-based workflows implemented in different tools

Examples: Kubeflow

- **End-to-end orchestration**
- **Pipeline orchestration is based on workflows**
  - Argo Workflow
- **Training and serving operator abstractions**
  - low level training/serving tasks via different frameworks

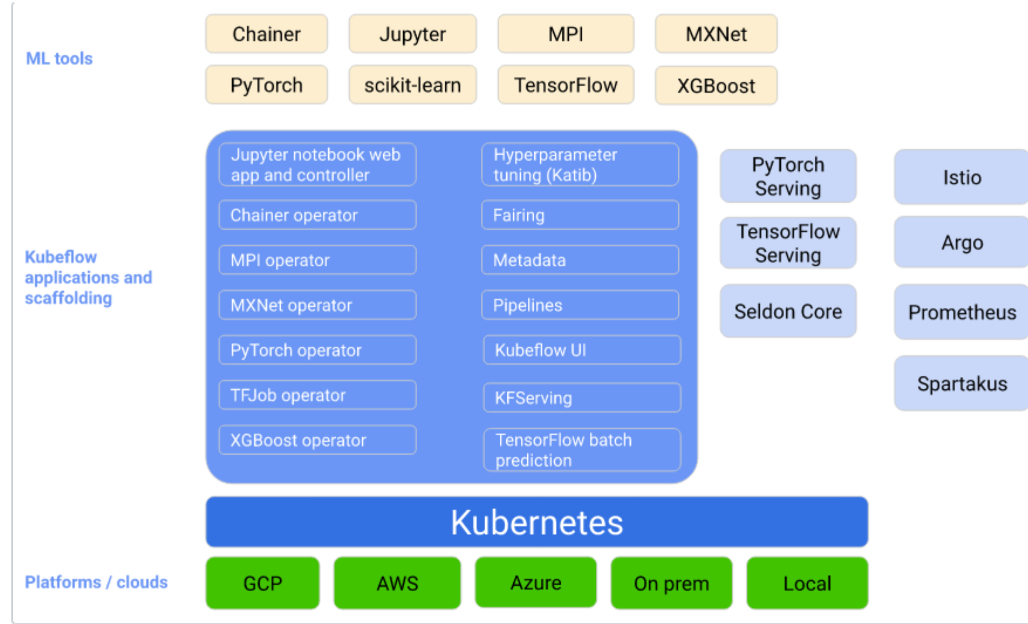
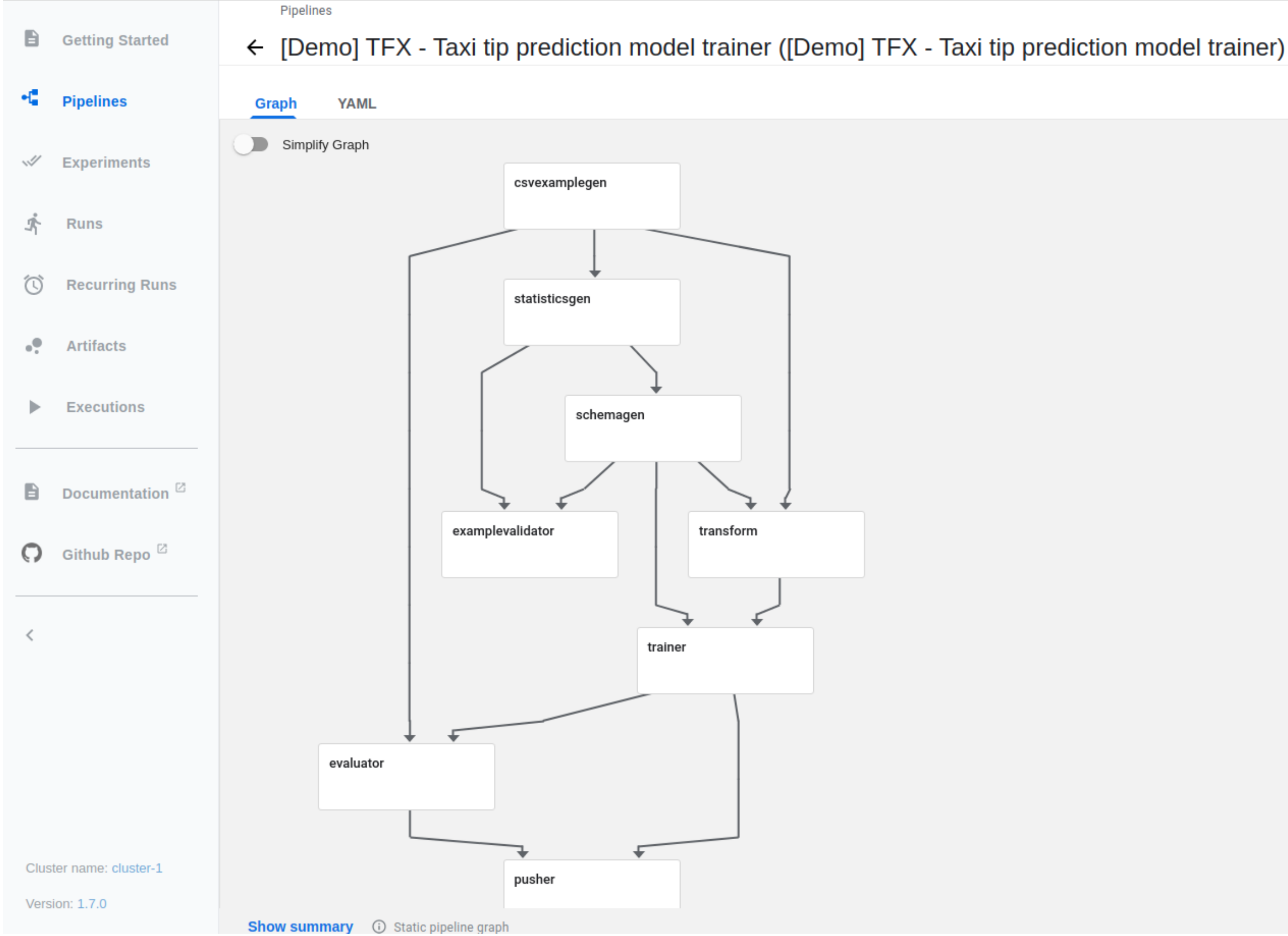


Figure source: https://www.kubeflow.org/docs/started/kubeflow-overview/

Captured from Kubeflow



Example: serverless as functions within ML workflows

- **Tasks in ML can be implemented as a function**
- **A workflow of functions can be used to implement ML pipelines**
  - Using serverless to implement data preprocessing/training
  - Serverless functions for inferences

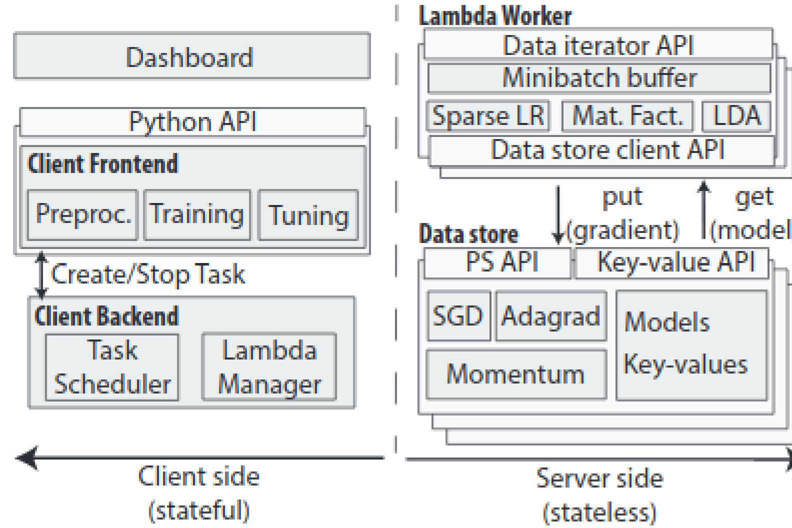


Figure source: Joao Carreira, Pedro Fonseca, Alexey Tumanov, Andrew Zhang, and Randy Katz. 2019. Cirrus: a Serverless Framework for End-to-end ML Workflows. In Proceedings of the ACM Symposium on Cloud Computing (SoCC '19). DOI:https://doi.org/10.1145/3357223.3362711

Discussion: why workflows are good for big data/ML?

- **One workflow for all or separate ones?**
  - for coordinating big data/ML phases/stages in the pipeline
- **Many possible different tasks but what are challenges?**
  - data preprocessing tasks and training tasks
  - experiment management
  - batch model for machine learning serving
  - resources provisioning
- **Which ones should we choose?**
  - separate – as a framework/service
  - integrated within big data/ML frameworks

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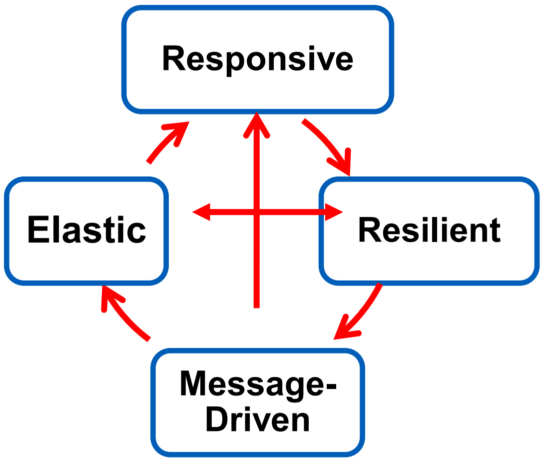
Coordination with messaging

The reactiveness style

Choreography: reactive systems for Big Data/ML

Reactive systems



Source: https://www.reactivemanifesto.org/

- Responsive: quality of services
- Resilient: deal within failures
- Elastic: deal with different workload and quality of analytics
- Message-driven: allow loosely coupling, isolation, asynchronous

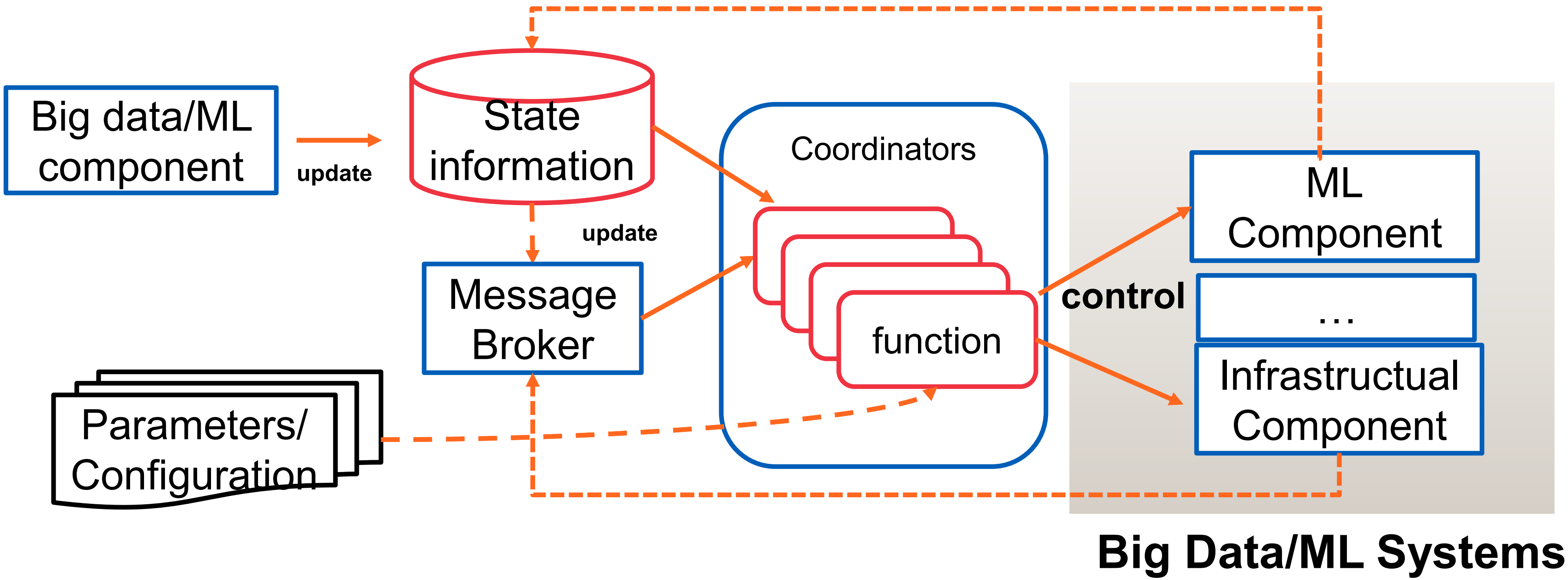
Reactive systems for Big Data/ML: methods

- **Have different components as services**
  - components can come from different software stacks
  - components for doing computation as well as for data exchange
- **Elastic computing platforms**
  - platforms should be deployed on-demand in an easy way
- **Using messages to trigger tasks carried out by services**
  - messages for states and controls as well as for data
  - heavily relying on message brokers and lightweight triggers/controls (e.g., with serverless/function-as-a-service)

Which frameworks?

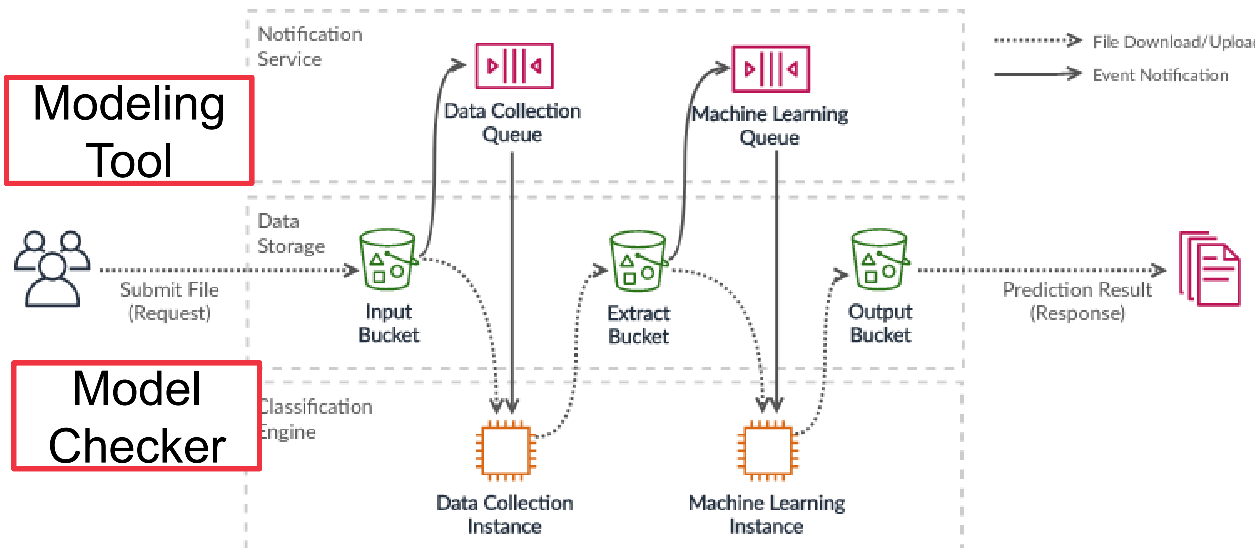
- **Low level messaging systems**
  - Kafka, RabbitMQ, ZeroMQ, Amazon SQS, …
  - types of messages and semantics must be defined clearly
- **Triggers and controls**
  - The serverless/function-as-a-service model: trigger a function/task based on a message
    - *AWS Lambda, Google Cloud Function, Knative, Kubeless, OpenFaaS, Azure Functions*
    - *We are discussing to use serverless for "coordination"*
  - The worker model: a light weighted service listening messages to trigger functions/tasks (can be remote)

Common architecture



Examples: do-it-your-self ML classification for BIM

- Discussion: dealing R3E with ML workflows?
  - Where, What, When and How



Source: Minjung Ryu, „Machine Learning-based Classification System for Building Information Models", Aalto CS Master thesis, 2020
Ryu, M., Truong, HL. & Kannala, M. Understanding quality of analytics trade-offs in an end-to-end machine learning-based classification system for building information modeling. J Big Data 8, 31 (2021). https://doi.org/10.1186/s40537-021-00417-x

Example: Serverless for coordination

- **Training preparation**
  - before running a training: you move data from sources to stage, ship the code and prepare the environment
- **Coordination of ML phases**
  - do the coordination of three phases: data preprocessing, training and take the best model to deploy to a serving platform
- **Experiment results gathering**
  - you run experiments in different places. There are several logs of results, you gather them and put the result into a database

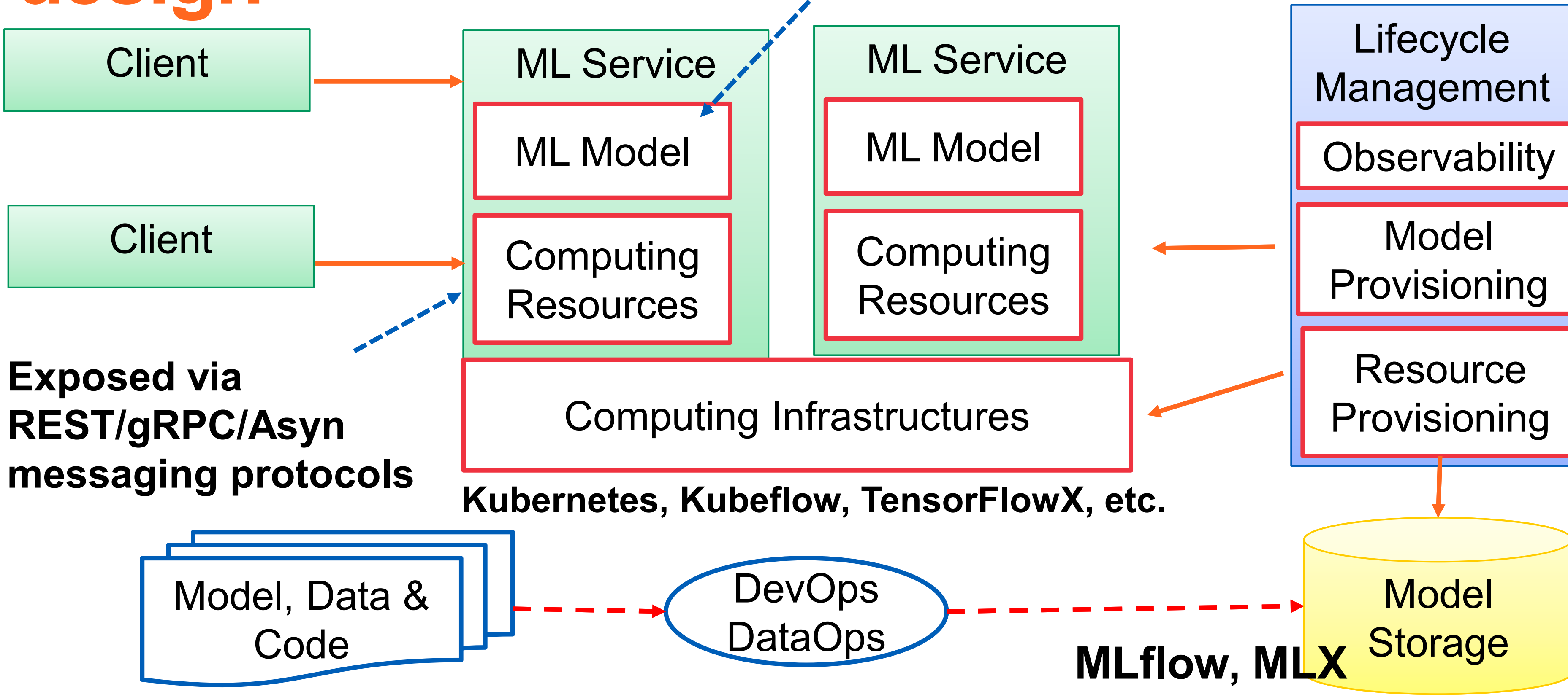
Dynamic ML Serving

ML model serving

- **Allow different versions of ML models to be provisioned**
  - runtime deployment/provisioning of models
  - "model as code" or "model as a service" → can be deployed into a hosting environment
- **Why? Anything related to R3E?**
  - concurrent deployments with different SLAs
  - A/B testing and continuous delivery for ML (https://martinfowler.com/articles/cd4ml.html)
- **Existing platforms**
  - increasingly support by different vendors as a concept of "AI as a service" (check https://github.com/EthicalML/awesome-production-machine-learning#model-deployment-and-orchestration-frameworks)

ML Model Serving design

Different integration techniques (containerization, external process execution, in-process execution)



ML Service

- **Long runtime inferencing services**
  - with well defined interfaces, know how to invoke models
  - accept continuous requests and serve in near-real time
- **Containerized service with REST/gRPC and messaging protocols**
  - for on-demand serving or for scaling long running serving
- **Serverless function wrapping models**
  - short serving time
- **Batch serving**
  - not near real time serving due to the long inferencing time

Question: which forms are the best for which situations? What about the underlying distributed computing for ML services?

Key technical features

- **Endpoint exposing**
  - ML model -> serving unit -> composition of units (dependency graph or horizonal/relica models) -> APIs
- **Serving handles:**
  - different function of routing, composition, load balancing
  - common techniques: HTTP/gPRC proxy, elasticity controller, replica management, and underlying infrastructure orchestrator
- **Serving (dynamically) loads (updated) models**
- **Coupled with deployment configuration**
  - given deployment tools can decide how to deploy serving units
- **Serving platform/toolkits: Ray, BentoML, Seldon, etc.**

Example of exposing ML models

BentoML

```python
import numpy as np
import bentoml
from bentoml.io import NumpyNdarray

iris_clf_runner = bentoml.sklearn.get("iris_clf:latest").to_runner()

svc = bentoml.Service("iris_classifier", runners=[iris_clf_runner])

@svc.api(input=NumpyNdarray(), output=NumpyNdarray())
def classify(input_series: np.ndarray) -> np.ndarray:
    result = iris_clf_runner.predict.run(input_series)
    return result
```

Source: https://docs.bentoml.org/en/latest/concepts/service.html

Ray serving

```python
from transformers import pipeline


@serve.deployment(num_replicas=2, ray_actor_options={"num_cpus": 0.2, "num_gpus": 0})
class Translator:
    def __init__(self):
        # Load model
        self.model = pipeline("translation_en_to_fr", model="t5-small")

    def translate(self, text: str) -> str:
        # Run inference
        model_output = self.model(text)

        # Post-process output to return only the translation text
        translation = model_output[0]["translation_text"]

        return translation

    async def __call__(self, http_request: Request) -> str:
        english_text: str = await http_request.json()
        return self.translate(english_text)
```

Source: https://docs.ray.io/en/latest/serve/getting_started.html

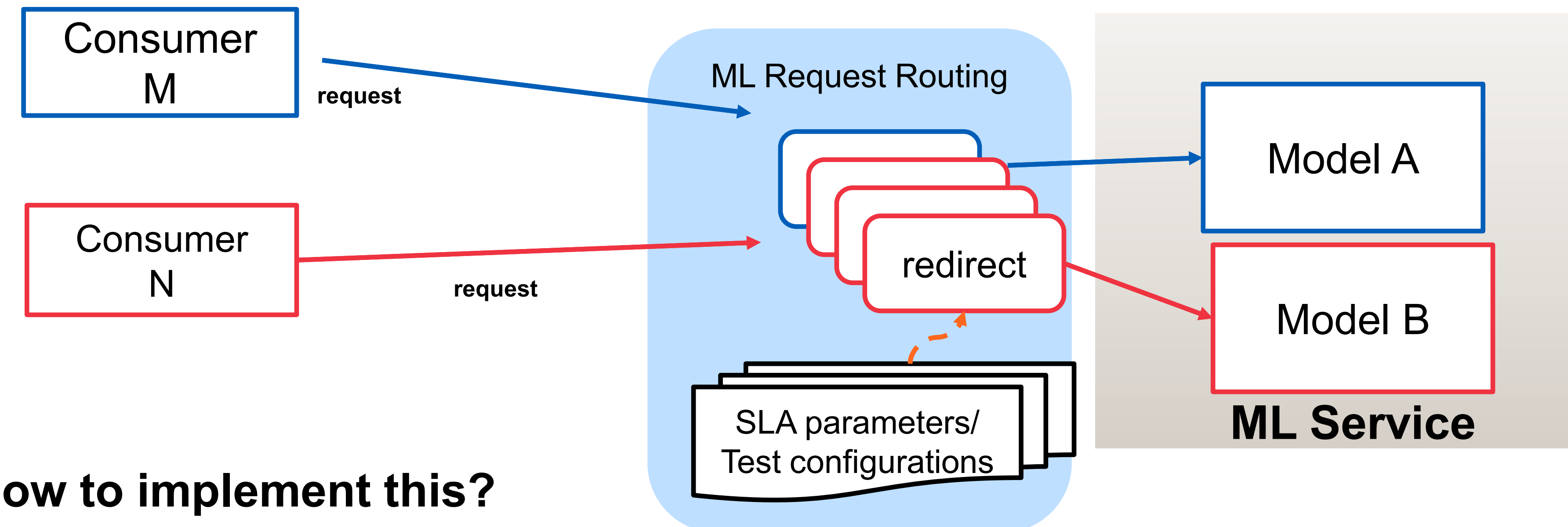
Tensorflow Serving

```
tensorflow_model_server --port=8500 --rest_api_port=8501 \
  --model_name=${MODEL_NAME} --model_base_path=${MODEL_BASE_PATH}/${MODEL_NAME}
```

Source: https://github.com/tensorflow/serving/blob/master/tensorflow_serving/g3doc/docker.md

A/B testing and SLA-based serving

- **Different models with different qualities/SLAs (R3E topics)**



How to implement this?

Example in Amazon Sagemaker

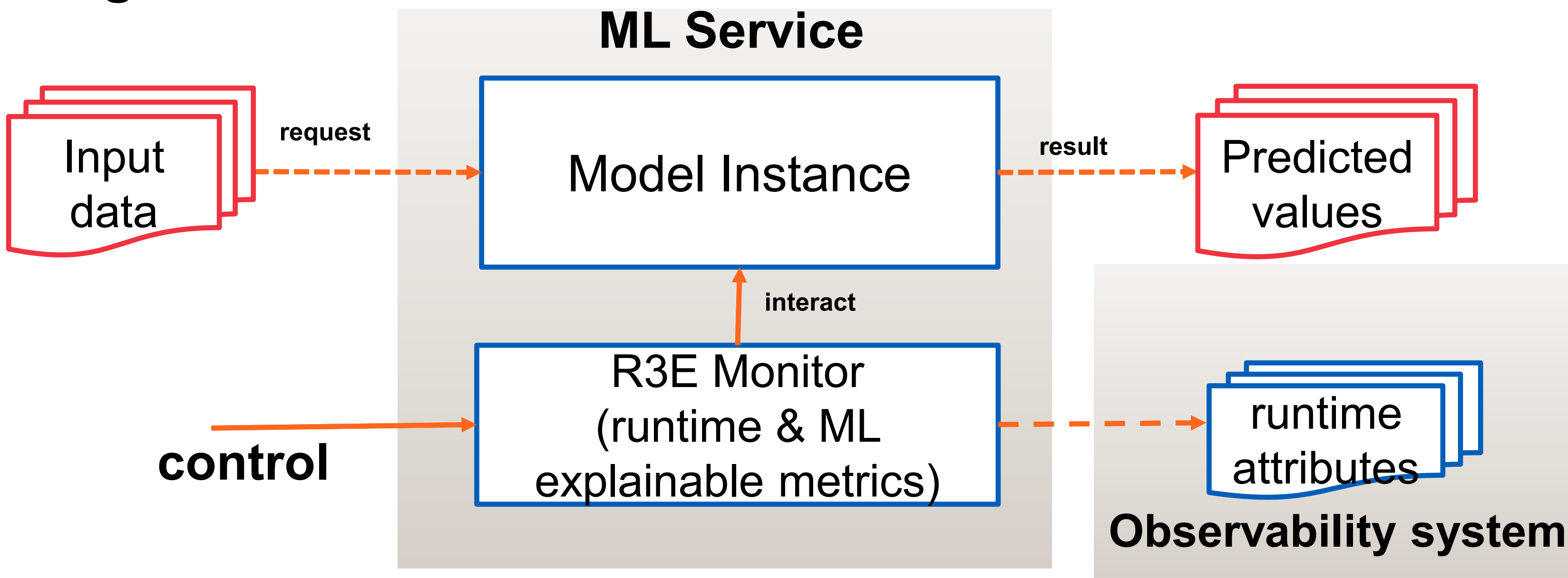
https://docs.aws.amazon.com/sagemaker/latest/dg/model-ab-testing.html

Load balancing/scaling model serving

- **ML inferencing capability in a ML model is encapsulated into a microservice or a task**
- **As a service**
  - with well-defined APIs (e.g., REST, gRPC), e.g., Dockerized service
  - using load balancing and orchestration techniques, such as Kubernetes
- **As a task**
  - using workflow management techniques to trigger new tasks
  - support scheduling, failure management and performance optimization by leveraging batch processing techniques

R3E runtime attributes?

How to capture important metrics for observability and dynamic serving?



Where are the difference in ML serving?

We can see common techniques like autoscaling, handles for encapsulating details & separation, proxy, multitenancy, etc.

But where would be the key different problems in ML serving?

Example: Ray Serving

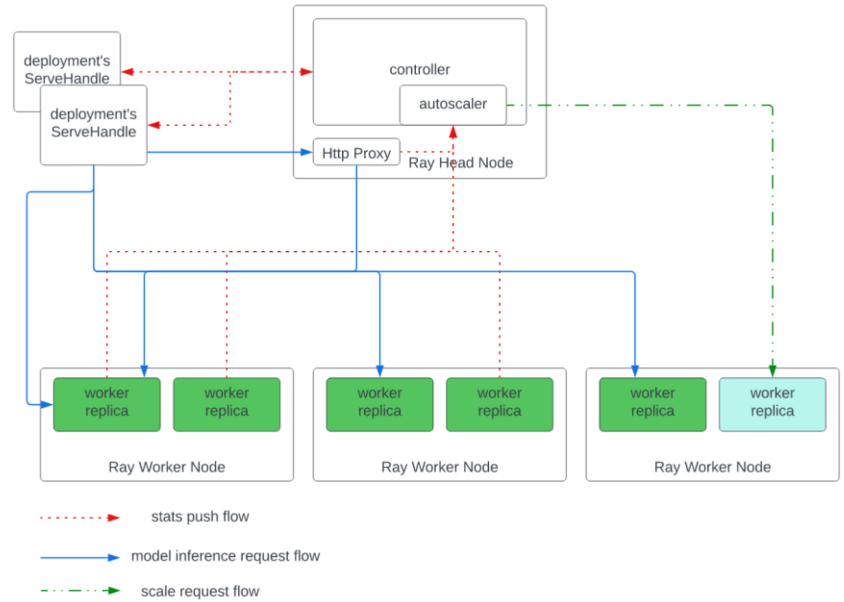


Figure source: https://docs.ray.io/en/latest/serve/architecture.html

Study log

P1 - Take one of the following aspects:

- P1.1 - Robustness, Reliability, Resilience or Elasticity
- P1.2 – Automation management

P2 - Check one of the following aspects:

- Orchestration of ML pipelines or ML model serving

In a *specific software framework* (F3) that you find interesting/relevant to your work:

discuss how do you see F3 supports P1 in doing P2

(the reading list also helps)

Thanks!

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